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Analysis of the procedures used to evaluate suicide crime scenes in Brazil: A statistical approach to interpret reports

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ABSTRACT

This study uses statistical techniques to evaluate reports on suicide scenes; it utilizes 80 reports from different locations in Brazil, randomly collected from both federal and state jurisdictions. We aimed to assess a heterogeneous group of cases in order to obtain an overall perspective of the problem. We evaluated variables regarding the characteristics of the crime scene, such as the detected traces (blood, instruments and clothes) that were found and we addressed the methodology employed by the experts. A qualitative approach using basic statistics revealed a wide distribution as to how the issue was addressed in the documents. We examined a quantitative approach involving an empirical equation and we used multivariate procedures to validate the quantitative methodology proposed for this empirical equation. The methodology successfully identified the main differences in the information presented in the reports, showing that there is no standardized method of analyzing evidences.

1. Introduction

The initial approach to the crime scene is crucial to case-solving. However, the resources available to each jurisdiction vary.[1] In Brazil, approaches to crime scenes differ even for crimes of the same type. Because desirable uniformity is lacking, a series of questions regarding the procedures for crime-scene analysis and their results may arise. Analysis of material evidence requires greater technical precision to improve the investigative process. Some isolated efforts already exist with respect to creating regulations to standardize the procedures to be adopted at crime scenes.[2] In the USA, for example, the National Institute of justice provides guidelines for crime scene investigation.[3–5]

While homicide consists of killing someone else, suicide is the act of deliberately taking your own life. Many reasons may lead a person to commit suicide, including mental disorders and some physical illnesses.[6] For the USA National Center for Injury Prevention and Control, suicidal self-directed violence is the "*Behavior that is self-directed and deliberately results in injury or the potential for injury to oneself. There is evidence, whether implicit or explicit, of suicidal intent.*"[7] Murdering someone and committing suicide are extreme acts of aggression that shock, amaze, and affect society and the closest survivors, as well as the nation's economy. For justice and investigation purposes, establishing the difference between these behaviors is essential to clarify and define the dynamics in a crime scene. International or intercultural comparisons of suicide methods help to gain deeper understanding of the interplay between these two factors, and provide a basis for preventive strategies.[8]

Although the legal and psychological distinctions between homicide and suicide seem to be straightforward, the differential diagnosis of these two forms of violent death is no easy task for the experts during the analysis of a crime scene, especially in cases of suicide simulation. The specialized literature contains reports on cases in which it is difficult to ascertain whether the action is

Abbreviations: RR, Report Relevance; W_v, Variable Weight; F_c, Context Factor; PCA, Principal Component Analysis; KNN, K-th Nearest Neighbor; SIMCA, Soft Independent Modeling of Class Analogies; PLS, Partial Least Squares; LOO, Leave One Out; LNO, Leave N-Out; RMSEV, Root Mean Square Error of Validation; RMSEC, Root Mean Square Error of Calibration.

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homicide, suicide, or accident.[9] Additionally some papers have described suspicious and simulated suicide[10,11]; in very singular situations, homicide simulation can occur.[12]

Despite the complexity of the analysis, experts may reach a satisfactory conclusion about the cause of death if they examine the crime scene thoroughly and identify traces generated during the violent action correctly. The individual analysis of traces and their connection are key to establishing crime dynamics and the criminal's mode of action.

Advances in scientific methodology have influenced the development of expertise in the sense of avoiding biased interpretation. Scientists have improved technical tests which have made forensic investigation more reliable. Scientific methods, specific protocols, statistical tools, and other objective criteria are important in establishing and strengthening forensic work as a science.[13]

When a criminal offense is committed, all the evidence should be assessed jointly. This should be collected and evaluated in order to determine the identity of the criminal.[14] Forensic investigation involves applying a scientific method to crime investigation and provides vital, objective information about the case. Forensic examination consists of the following phases: recognition, identification, comparison, individualization and interpretation of tests.[15]

Recent advances in science and technology have provided forensic scientists with a vast number of methods and techniques. When experts assess the physical evidence, they gather it together and quantify the contribution of a particular suspect in the event. To solve this problem, many experts employ statistical tools in order to interpret the results. Statistical analysis of forensic data has acquired growing importance in courts. Forensic scientists can now evaluate and interpret the evidence that includes elements of uncertainty.[14,16] The literature also reports cases of subjectivity bias is registered on fingerprint and DNA analysis.[17–19]

This study aims to examine expert reports of crime scenes of suicide by using statistical tools to assess the gaps and weaknesses in the procedures described in the reports. Our overall is to gain an idea of the dimension of the problem and offer some positive feedback to official expertise, showing the need to design a standardized procedure for the analysis of crime scenes related to violent deaths in Brazil.

2. Material and methods

Eighty reports of suicide were analyzed after being randomly collected from different jurisdictions and locations. The objective was to evaluate a heterogeneous group of cases to formulate an overview of the analysis.

The first step was to determine the cause of death in each case and then formulate questions about the methodology. There were 19 variables, associated with the questions listed in Table 1. The possible answers were YES, NO or Impossible to Determine (ID), which were attributed values 1, −1 and 0, respectively. A NO answer could account for something that should have existed and constitutes a negative factor for the item. Impossible to Determine, refers to situations when it was not possible to identify any YES or NO answers for the variable, due to lack of information in the report. For example, if the report did not cite clothes, analysis of this variable was impossible. However, this does not mean that experts did not analyze the variable; it only meant that the information did not exist in the report.

From these variables, the overall quality of each report was calculated using the following auxiliary variables:

Report Relevance (RR) determines how representative the report was in terms of the information that it contains; an empirical equation was developed; two parameters were elaborated: Variable Weight and Context Factor.

Table 1
Variables studied in the analysis.

V01	Were injuries characterized in the report?
V02	Did the report contain details about these injuries?
V03	Was the violent act performed by means of an instrument?
V04	Was the instrument collected?
V05	Was the instrument analyzed?
V06	Did the report describe the absence of typical lesions related to fighting or defense?
V07	Were the victim's clothes mentioned?
V08	Were the victim's clothes analyzed?
V09	Was blood at the scene mentioned?
V10	When found, were the bloodstains analyzed?
V11	Was the body position described?
V12	Was the body position related to the dynamics of the facts?
V13	Did the report present a dynamic compatible with the evidence at the crime scene that could rule out homicide (suicide simulation)?
V14	In addition to the tests performed at the scene, were additional laboratory tests conducted?
V15	Did the report discuss the characteristics of the scene?
V16	Is there a classification regarding the characteristics of the crime scene? (*e.g.* reputable or disreputable; mediate, immediate or related etc.)
V17	Was the evidence of violence photographed?
V18	Did the report show a sketch to enable better understanding of the facts?
V19	Did the report use appropriate language (clear, objective, and grammatically correct)?

Variable Weight (*Vw*) is intended to correct distortions regarding the importance of each variable, associated with a numerical value according to the importance of the information, *i.e.*, how significant the specific condition is for the report. The weights were set as 1 when the variable was considered as **relevant**, 2 when it was assigned as **necessary** and 3 when it was considered to be **fundamental**. Table 2 lists explanations of these values in the case of each variable.

Context factor (*F*$_c$) is a means of pondering each variable considering the context of the criminal action. It is specific to each report and provides a more sensitive analysis, because the situation can affect the relevance of the variables. For example: the analysis of the instrument was considered to be fundamental, but if the cause of the death was human fall, no further analysis was necessary. In this situation, although the variable is important, its absence is completely acceptable. The same applies if a gun was found to have been used in the crime scene, but the cause of the death was hanging and no bullet wounds are found on the body. In this context, the gun analysis is relevant but not necessarily associated with the case. *Fc* values were 0 for **irrelevant**, which means that the answer does not apply to the studied case; 1 for **relevant**; 2 for **necessary** and 3 when it was considered **fundamental**.

The parameters described above were developed to provide an empirical equation for Report Relevance, given by:

$$RR = \frac{\sum_{i=1}^{n} Wv(i)Fc(i)Vq(i)}{\sum_{i=1}^{n} Wv(i)Fc(i)}, \tag{1}$$

where *Vq* is the variable of the question (sum of answers to the formulated variables). RR ranges from 0 to 1. This equation seeks to provide a quantitative indication of the amount of the information accounted for in each report.

In order to test if *RR* makes sense, it was validated using the following multivariate tools:

a) **Pattern recognition** was used to identify the characteristics of the data set and associate similarities among the data. This was achieved by observing natural clustering (unsupervised

Table 2
Variable weight and reason for relevance. The values are associated to: (1) relevant, (2) necessary, and (3) fundamental.

Variable	Weight	Reason for relevance
V01	2	Injuries provide vestiges of the event dynamics.
V02	3	These details provide essential vestiges for the investigation.
V03	1	The instrument is important, but its absence does not jeopardize the report.
V04	2	The instrument provides ways of extracting information that can be decisive.
V05	3	Instrument analysis is a direct source of important information.
V06	3	It is fundamental to disqualify the event as suicide. The absence of this description may invalidate the credibility of the entire report.
V07	1	This information is required, but its mention does not add much to the case.
V08	2	The evaluation of clothes can be an important source of evidences.
V09	1	This information is required, but its mention does not add much to the case.
V10	3	All the evidence derived from blood studies depends on this analysis.
V11	2	Description of the body position helps to establish the criminal dynamics.
V12	3	The relationship of the body's position and the criminal dynamics is hoghly important in solving the case.
V13	3	If this dynamic is not determined, the report may be completely mischaracterized.
V14	2	The complementary exams can detect vestiges that may be necessary for case-solving.
V15	1	Place description is required.
V16	1	This information can be helpful in interpret the criminal's dynamics.
V17	2	Photographic evidence may generate new evidence or help re-interpretation.
V18	2	The sketch may generate new evidence or help re-interpretation.
V19	1	Appropriate language and spelling are required.

learning) or by using classification techniques (supervised learning).

b) **Partial Least Square (PLS)** was applied to data considering RR the dependent (or projection) variable. The main objective was to identify which variables were more important in the composition of RR values.

Table 3
Mode used in the suicidal action.

A	Hanging	45
B	Injury by blunt-piercing instrument	16
C	Impact due to fall from great height	8
D	Poisoning	4
E	Not clear in the report	4
F	Injury by cutting and piercing instrument	3
G	Drowning	1

2.1. Pattern recognition

Exploratory analysis or unsupervised learning can help to evaluate natural similarities. The main goal is to display extensive and complex data by reducing the system's dimensions, which provides a better understanding of the structure and the correlations among samples and the variables in the data set.[20] This paper uses the following techniques:

- *Principal Component Analysis* (PCA), which is a multivariate method that can verify similarities among samples by reducing the system's dimension.[21–23]
- *Hierarchical Cluster Analysis* (HCA), which is a multivariate method for unsupervised learning.[21,24,25] Its goal is to display data in a two-dimensional space, to emphasize their natural clustering and patterns.
- Supervised learning methods to assign samples into pre-defined classes and check the efficiency of this classification. This class of modeling techniques have many variations, but we only use the K-th Nearest Neighbor (KNN)[20,26] and the flexible modeling method known as SIMCA (Soft Independent Modeling of Class Analogies).[20]

Partial Least Squares is a regression method that is often employed to validate models[27–29] and is particularly important in the present study. In our case, the data matrix $\boldsymbol{X}$ contains samples (rows, for each report) and variables (columns, the questions) and at least one vector $\boldsymbol{RR}$ – called the dependent variable - featuring data on the properties. The main assumption is that a linear combination of the information matrix $\boldsymbol{X}$ can describe the dependent variable $\boldsymbol{RR}$. The regression vector β indicates which

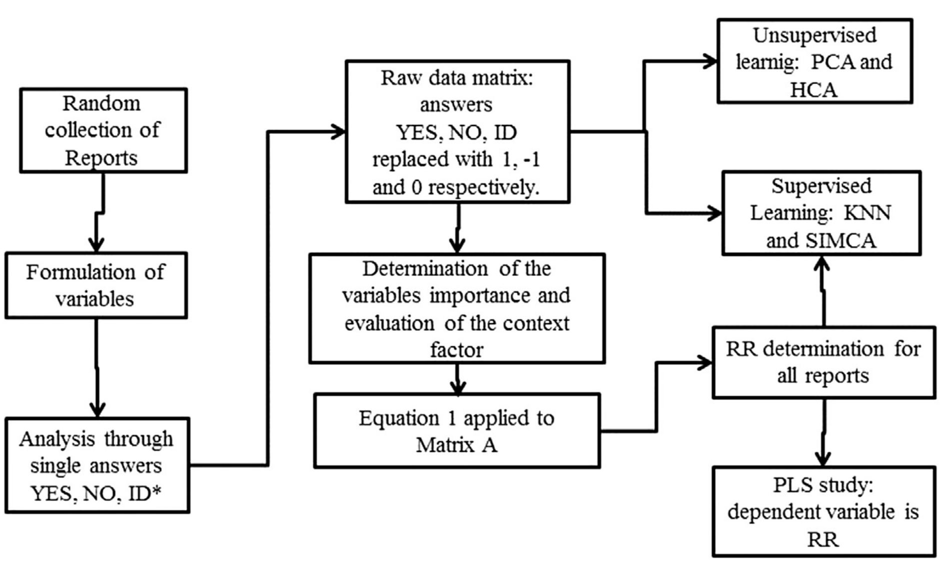

Fig. 1. Scheme for reports evaluation.

Table 4
Total YES, NO and ID.

	V01	V02	V03	V04	V05	V06	V07	V08	V09	V10
YES	66	46	69	26	40	49	68	17	27	21
NO	9	21	4	43	29	29	10	61	53	9
ID	5	13	7	11	11	2	2	2	0	50
	V11	**V12**	**V13**	**V14**	**V15**	**V16**	**V17**	**V18**	**V19**	
YES	66	48	50	19	77	35	79	16	79	
NO	13	26	27	61	3	45	1	63	1	
ID	1	6	1	0	0	0	0	1	0	

descriptors are important in modeling ***RR*** (Equation (3)). The principal components are "optimized" to better describe the relationship between the matrix ***X*** and the vector ***RR*** simultaneously.

$$y = X\beta \tag{2}$$

Validation is necessary to ensure the robustness and predictive ability of the model, as well as its use with samples that were not part of the calibration step. In this case we performed from Leave One-Out (LOO) up to Leave Seven-Out cross-validations.[30]

To strengthen the modeling, some useful indicators must be evaluated:

- Internal correlation coefficient model cross-validation (Q^2), given by

$$Q^2 = 1 - \left(\frac{\sum_i (y_{ei} - y_{vi})^2}{\sum_i (y_{ei} - <y_e>)^2}\right) \tag{3}$$

- Correlation coefficient for calibration (R^2), given by

$$R^2 = 1 - \left(\frac{\sum_i (y_{ei} - y_{ci})^2}{\sum_i (y_{ei} - <y_e>)^2}\right) \tag{4}$$

- Root Mean Square Error of Validation (RMSEV), given by

$$\text{RMSEV} = \sqrt{\sum_i \frac{(y_{ei} - y_{vi})^2}{n}} \tag{5}$$

- Calibration (RMSEC), given by

$$\text{RMSEC} = \sqrt{\sum_i \frac{(y_{ei} - y_{ci})^2}{n}} \tag{6}$$

where n is the number of samples, y_e the original data, y_c the value obtained from calibration and y_v the value calculated during cross-validation. Correspondence statistics are characterized by the

Table 5
Number of YES, NO and ID answers for the individual reports.

	R01	R02	R03	R04	R05	R06	R07	R08	R09	R10	R11	R12	R13	R14	R15	R16	R17	R18	R19	R20
YES	16	10	16	16	9	19	16	17	19	9	10	11	4	8	10	6	7	8	7	10
NO	3	7	3	2	6	0	3	2	0	10	7	5	13	9	8	12	11	10	11	9
ID	0	2	0	1	4	0	0	0	0	0	2	3	2	2	1	1	1	1	1	0
	R21	**R22**	**R23**	**R24**	**R25**	**R26**	**R27**	**R28**	**R29**	**R30**	**R31**	**R32**	**R33**	**R34**	**R35**	**R36**	**R37**	**R38**	**R39**	**R40**
YES	5	7	7	9	2	9	13	6	5	8	6	6	8	7	5	9	17	11	9	12
NO	12	11	10	10	9	7	5	8	14	8	11	12	10	11	12	9	2	7	10	6
ID	2	1	2	0	8	3	1	5	0	3	2	1	1	1	2	1	0	1	0	1
	R41	**R42**	**R43**	**R44**	**R45**	**R46**	**R47**	**R48**	**R49**	**R50**	**R51**	**R52**	**R53**	**R54**	**R55**	**R56**	**R57**	**R58**	**R59**	**R60**
YES	13	17	13	18	14	12	10	14	14	13	12	11	11	12	11	14	12	12	13	9
NO	5	2	6	1	5	7	8	4	4	5	4	7	7	6	4	4	4	4	5	6
ID	1	0	0	0	0	0	1	1	1	1	3	1	1	1	4	1	3	3	1	4
	R61	**R62**	**R63**	**R64**	**R65**	**R66**	**R67**	**R68**	**R69**	**R70**	**R71**	**R72**	**R73**	**R74**	**R75**	**R76**	**R77**	**R78**	**R79**	**R80**
YES	13	14	16	12	13	15	11	13	18	13	10	9	11	13	15	11	11	12	11	17
NO	5	4	3	4	5	4	4	3	1	5	8	9	7	6	4	3	7	6	7	0
ID	1	1	0	3	1	0	4	3	0	1	1	1	1	0	0	5	1	1	1	2

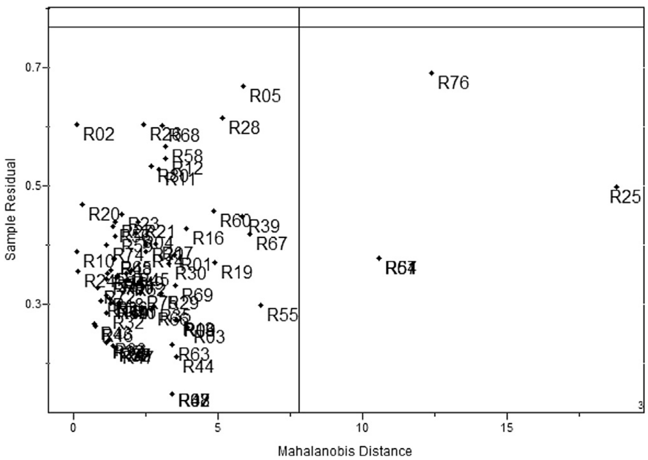

Fig. 2. Outlier detection.

relation $R^2 > Q^2$ and RMSEC < RMSEV. Fig. 1 depicts the procedure used for analysis of the reports. All multivariate methods were performed with the Pirouette® package.[31]

3. Results

3.1. Qualitative studies

The mode of suicidal action was evaluated for all reports; Table 3 summarizes the results. Hanging was the most common mode of action, followed by injury by blunt-piercing instrument, and impact due to fall from great height. Only one, four and three cases concerned death by drowning, poisoning and injury by cutting and piercing instrument, respectively. The cause of death was not identified in four cases. Table 4 contains the answer YES, NO and ID for each variable.

Table 4 shows most of the variables (V01, V02, V03, V05, V06, V07, V11, V12, V13, V15, V17 and V19) presented YES answers. However, none of the variables obtained 100% YES answers, demonstrating that no variable was found as positive for all the reports. See the complete results Table in Supplementary Information (Tables 1.1–1.4).

Table 5 lists the total number of YES, NO and ID answers in each report. Pareto's Diagrams for each block of twenty reports are shown in the Supplementary Information (Figs. 1–4). The results reveal that only two reports (R06 and R09) had 100% positive aspects, *i.e.*, they contained only YES answers, corresponding to 2.5% of the total of number of reports analyzed herein. Twenty reports (R10, R13, R14, R16, R17, R18, R19, R21, R22, R23, R24, R25, R28, R29, R31, R32, R33, R34, R35 and R39) obtained NO for most of the answers, indicating that these reports had more negative than positive aspects. These reports accounted for 25% of the entire evaluated set. Finally, no ID answers existed in only twenty-two reports (R01, R03, R06, R07, R08, R09, R10, R20, R24, R29, R37, R39, R42, R43, R44, R45, R46, R63, R66, R69, R74 and R75), demonstrating that, for most of the reports (around 72.5%), it was not possible to determine at least one variable.

3.2. Qualitative studies

We solved Equation (1) for the collected reports; Table 6 presents the Reports Relevance. Based on the results, the reports were classified into two classes:

- Class 1. RR values from 0.50 to 1.00 (RR ≥ 0.50): Reports contain more than the average amount of required information (black).
- Class 2. RR values from 0 to 0.50 (RR < 0.50): Reports contain less than the average amount of required information (red/grey/bold).

To try to validate the methodology suggested by Equation (1), we applied unsupervised learning techniques such as PCA and HCA

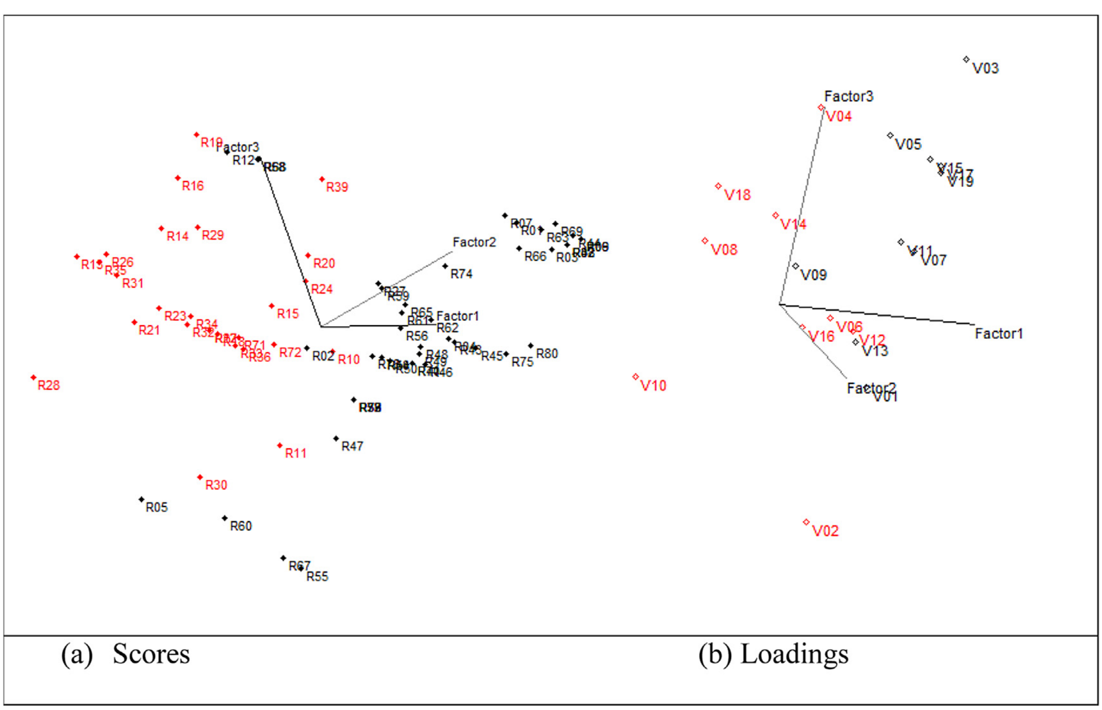

Fig. 3. Scores and loadings set for the three first principal components (Factor 1 × Factor 2 × Factor 3).

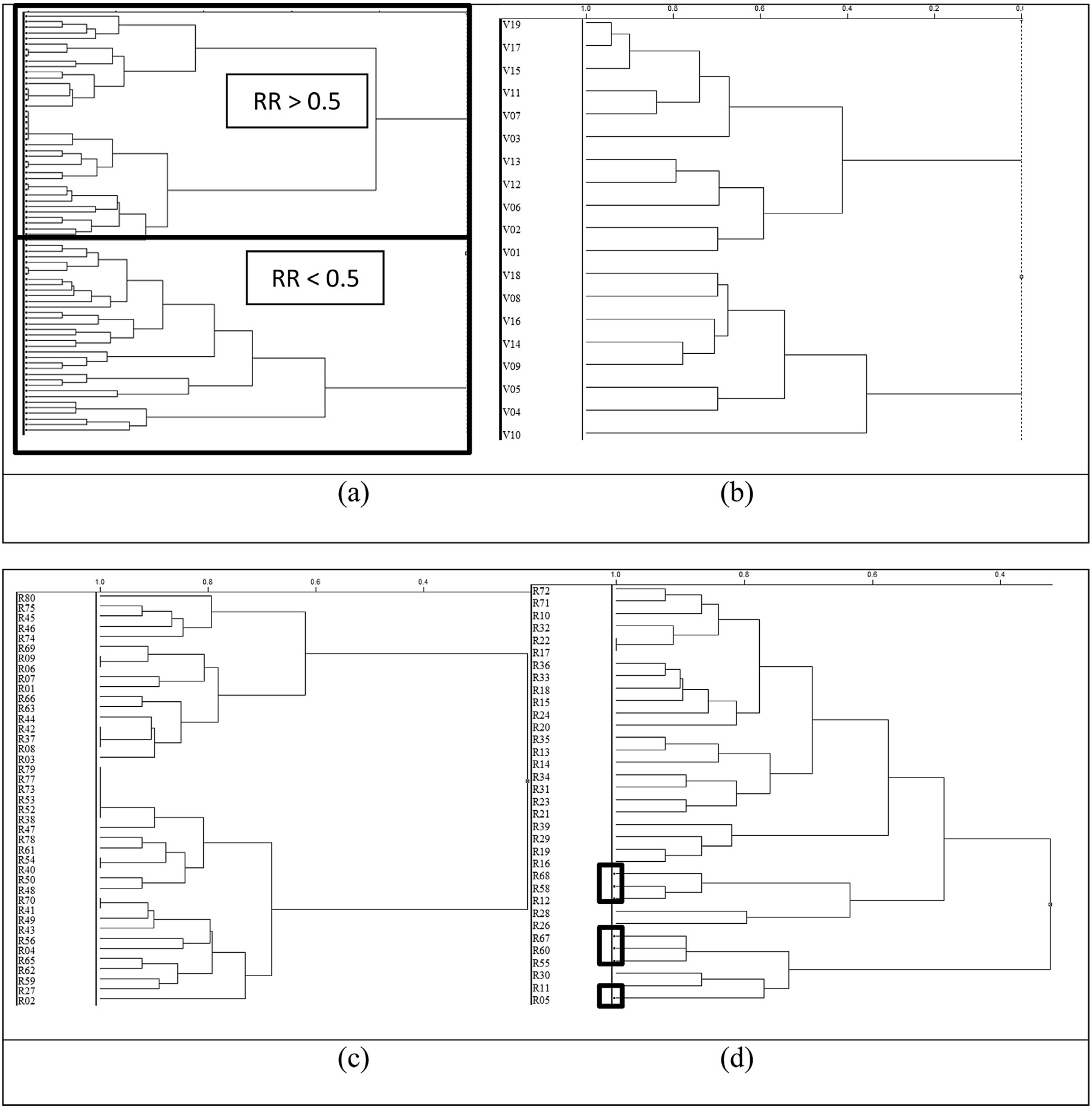

Fig. 4. HCA results for raw data matrix: (a) Samples clustering; (b) variables clustering; (c) zoom on the cluster with RR ≥ 0.50, numbers of each branch, from the top to the bottom are: R80, R75, R45, R46, R74, R69. R09. R06, R07, R01, R66, R63, R44, R42, R37, R08, R03, R79. R77, R73, R53, R52, R38, R47, R78, R61, R54, R40, R50, R48, R70, R41, R49, R43, R56, R04, R65, R62, R59, R27, R02, which correspond to the black reports in Table 6; (d) zoom on the cluster with RR < 0.50 (misclassified samples are highlighted), numbers of each branch, from the top to the bottom are: R72 R71 R10 R32 R22 R13 R36 R33 R18 R15 R24 R20 R35 R13 R14 R34 R31 R24 R21 R39 R29 R19 R16 R68 R58 R12 R28 R26 R67 R60 R55 R30 R11 R05, which correspond to the red/grey/bold reports in Table 6.

to the data. We also conducted classification by supervised learning SIMCA and KNN.

3.3. PCA results

We used PCA to validate the RR empirical equation. Firstly, we performed PCA on the raw data matrix, *i.e.*, the tri-valued matrix with 1, 0 and −1 data. We used the RR values to classify samples and employed this classification in comparisons with natural clustering.

We previously evaluated outliers by comparing sample residual with Mahalanobis Distance (Fig. 2). We removed five reports (R25, R76, R51, R57 and R64) from the data set, because they presented outlier behavior; this removal improved the PCA analysis. Fig. 3 depicts the 3-D scores–loadings pair of results from PCA for raw data matrix. Black and red/grey samples correspond to Class 1 and 2 respectively. Three principal components were able to separate the two classes and accounted for around 81% of all the information. Loadings (Fig. 3(b)) indicated that V10 was far from the other

variables and contributed to separating reports with RR < 0.50. V10 corresponded to the bloodstain analysis. Checking results for qualitative analysis, it is possible to note that most of the reports did not account for this evaluation. PCA loadings show that this variable V10 is really important for suicide analysis; its absence strongly influences reports with small RR values.

3.4. HCA results

We also used HCA to check clustering by the incremental method. Fig. 4(a) shows that two distinct groups can be identified: all the samples in the upper group showed RR ≥ 0.50 while, in the lower group, most of the samples displayed RR < 0.50. The variables V04, V05, V08, V09, V10, V14, V16 and V18 ranked the lowest with the relevant reports (RR < 0.50). The variable V16 referred to isolation and preservation of the crime scene, which are the first and fundamental requirements for successful technical and scientific research. The goal is to ensure that no evidence is inserted or withdrawn from the scene, which would change the interpretation of the facts.

An important element of documentation that must be present in the report is the sketch of the scene (V18), which gives a layout of the crime location, with evidence placed in the correct positions. The sketch complements the narration and photographs, and aids the understanding of the report.

When seeking a differential diagnosis between suicide and homicide, it is crucial to analyze the clothes (V08) and the instrument of violent action (V05). The garments on the body frequently provide important information and help to unravel the dynamics of the facts, such as identifying or excluding body fight before death. As for instruments, many can be used as weapons. The expert must collect (V04) for further analysis (V14), to determine the relationship between the injury and the instrument.

The variable analysis of bloodstains (V10) identified those reports that were considered unsatisfactory. The presence of bloodstains (V09) and their analysis allow the expert to evaluate the displacement of the victim at the scene, the intensity of the trauma and a possible aggressive position, among other inferences.

Both unsupervised techniques were able to provide a specific behavior for the studied classes. HCA had six misclassified samples, which corresponded to 8% of the whole set of reports. The variables accounting for report classification as unsatisfactory reports were the same: V04, V05, V08, V09, V10, V14, V16 and V18, agreeing with data from Table 4. Most of the reports lacked these variables: a higher number of reports contained NO and ID responses to these variables as compared with the number of reports with YES answers.

A detailed examination of class reports with RR < 0.50 showed that seven samples were misclassified (highlighted in Fig. 4(d), R05, R12, R55, R58, R60, R67 and R68). These misclassifications can be understood using Tables 1.1 to 1.4 (Supplementary Information), which indicate that these reports lacked a positive answer for the variables that led to RR < 0.50.

3.5. KNN results

As for KNN analysis, we did not use any preprocessing and we tested a maximum of neighbors. Fig. 5 shows the number of misses versus the neighbors. For three neighbors, we achieved optimal classification with 0 misses and a 0.95 probability threshold. If KNN is hard modeling, this result can be considered as a good classification - an optimal number of neighbors can classify reports without errors.

3.6. SIMCA results

For SIMCA we selected four Principal Components as being ideal for modeling with a 0.95 Probability Threshold. Figs. 6 and 7 bring scores for Class 1 and Class 2, respectively. R05 is far from the other samples, followed by R02, R12, R55, R58, R60, R67 and R68. Although these reports presented RR over 0.51, the red/grey variables influenced them (Fig. 8, Loadings). This led to their classification as Class 1, agreeing with PCA and HCA analyses. In the case of this class, four principal components account for 91% of the information. For Class 2, four principal components account for 87% of the entire information.

Table 6
Score obtained for each report from Equation (1).

R01	0.81	R21	0.16	R41	0.78	R61	0.82
R02	0.69	R22	0.20	R42	0.91	R62	0.84
R03	0.90	R23	0.23	R43	0.71	R63	0.81
R04	0.94	R24	0.30	R44	0.95	R64	0.82
R05	0.59	R25	0.06	R45	0.75	R65	0.72
R06	1.00	R26	0.44	R46	0.60	R66	0.76
R07	0.75	R27	0.66	R47	0.65	R67	0.72
R08	0.91	R28	0.43	R48	0.84	R68	0.91
R09	1.00	R29	0.18	R49	0.84	R69	0.89
R10	0.30	R30	0.38	R50	0.82	R70	0.78
R11	0.4	R31	0.21	R51	0.82	R71	0.22
R12	0.71	R32	0.15	R52	0.66	R72	0.33
R13	0.1	R33	0.32	R53	0.66	R73	0.66
R14	0.36	R34	0.24	R54	0.77	R74	0.70
R15	0.48	R35	0.16	R55	0.80	R75	0.76
R16	0.19	R36	0.37	R56	0.81	R76	0.79
R17	0.20	R37	0.91	R57	0.82	R77	0.66
R18	0.25	R38	0.66	R58	0.73	R78	0.71
R19	0.27	R39	0.35	R59	0.76	R79	0.66
R20	0.28	R40	0.77	R60	0.52	R80	1.00

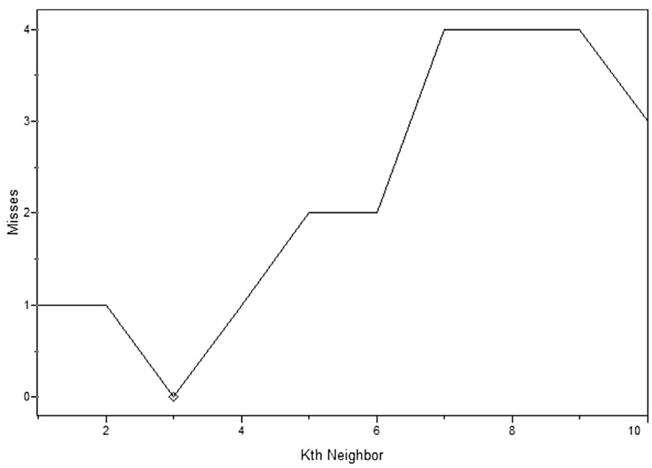

Fig. 5. Number of misses versus number of neighbors.

The distance between classes showed that the value was around 0.73 for the two assigned classes, *i.e.*, higher than the cutoff used to define the classes (0.50). The classes' residuals were higher when we fitted one class against the other one (Table 7), indicating good discriminating power.

The SIMCA modeling accounted for two misclassifications. R02, initially assigned as Class 1, was reclassified by SIMCA as Class 2. The opposite happened in the case of R39. In fact, for R02, most of the variables that led to RR < 0.50 had NO or ID answers. On the other hand, for R39, although it had RR < 0.50, these variables are mostly YES responses. The overall misclassification (2 reports in 75) represented less than 3% of the total number of reports. According to the literature, if a model classifies 95% of the samples correctly and if no class contains more than one misclassification, the results are highly acceptable.[20]

3.7. PLS results

We analyzed the raw data matrix against the RR score as a dependent variable. The main goal was to conduct a multiple regression with the variables, to examine how useful they are in the composition of RR values. In this case, it is not helpful to select variables; the goal is to verify which variables contribute the most to a satisfactory report.

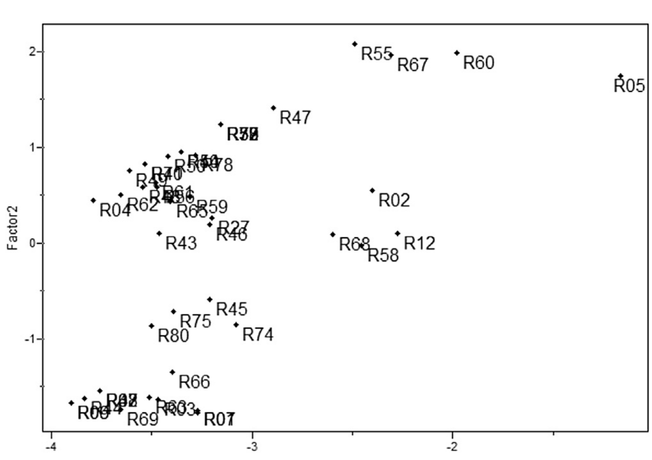

Fig. 6. Scores for class 1: RR ≥ 0.50.

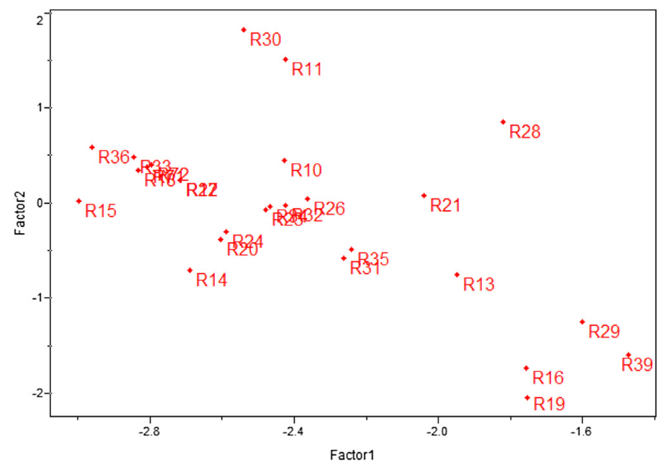

Fig. 7. Scores for class 2: RR < 0.50.

We accomplished modeling without pretreatment; we performed from Leave One Out (LOO) up to Leave Seven Out (LNO, $N = 7$) validations. The idea was to test the effect of removing around 10% of the total number of reports. All the models furnished the same results: we chose five principal components as optimal and accounted for around 86% of the whole set of information. Q^2 and R^2 values were 0.94 and 0.97, respectively. RMSEC was lower than RMSEV in all cases. The results confirmed that the values were robust – we obtained the same numbers for all validation tests. Hence, the RR equation can give an idea as to the amount of information in a report. The regression is presented in Fig. 9, which displays the two classes studied in very distinct regions. The regression vector and the coefficients for each variable are shown in Table 8.

Two variables contributed the most to the suitability of the reports: the presence or absence of defense lesions in the victim (V06) and the correlation between traces and dynamics of the facts (V13). These variables were inter-related and were essential to the

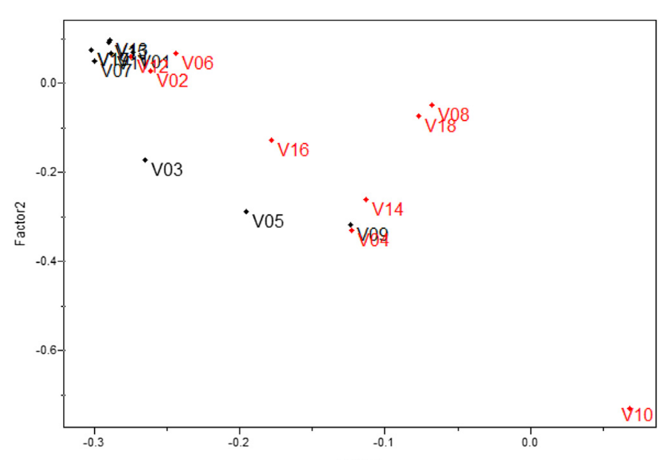

Fig. 8. Loadings for raw data matrix.

Table 7
Interclass residuals.

	Class 1	Class 2
Class 1	0.31	0.55
Class 2	0.49	0.30

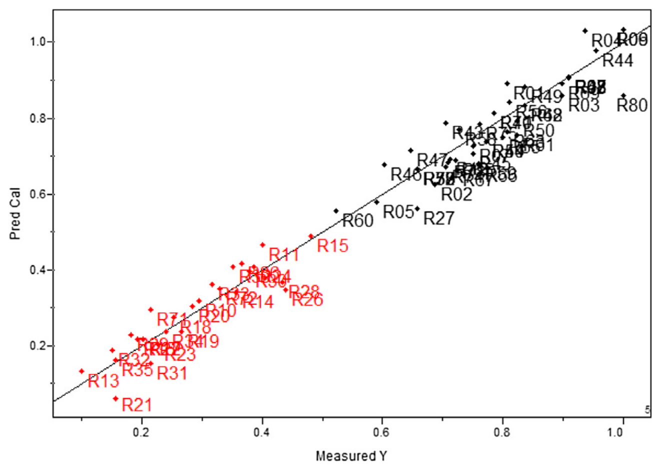

Fig. 9. Calibration curve for PLS regression.

differential diagnosis in the analysis of a suicide scene, helping to rule out the hypothesis of a simulation.

4. Conclusion

The aim of this study was to assess reports of suicide to determine the weaknesses of the procedures used by official expertise. We formulated 19 questions to evaluate the reports. These variables could be answered as YES, NO or ID (Impossible to Determine), which were assigned values 1, −1 or 0, respectively. The variable importance for the report was associated with the context of the situation, which was used in an empirical equation that calculated the Report Relevance (RR). We validated the RR equation using multivariate techniques (unsupervised HCA and PCA; supervised KNN and SIMCA), which discriminated between the classes assigned for RR < 0.50 and RR ≥ 0.50 with similar results. These techniques indicated that it was essential to analyze some variables in this type of crime scene, namely V04, V05, V08, V09, V10, V14, V16 and V18.

PLS analysis accounted for the RR values against the variables. LOO until LNO ($N = 7$) validation provided good values for Q^2 and R^2, around 0.94 and 0.97 respectively. Regression Vector revealed a major influence of variables V06 (absence of fighting signals) and V13 (matches between traces and dynamics) on the RR values. In fact, all other variables affected these ones in their evaluation.

According to the qualitative results, the way documents discussed the subject differed markedly, which can generate doubts in the case of litigation. In many cases, the conclusion had no clear correlation with the information in the set of presented evidence. The qualitative approach showed that no variable was dispensable in this study, and that the Report Relevance needs to consider the importance associated with the context of the crime scene.

Finally, we concluded that the suicide reports did not follow the any standardized methodology. This lack of reference procedure complicates the work of government experts. This study suggests that efforts toward the standardization of the procedures must be made. Standardization will entail more homogeneous results for analyses, thereby reducing the possibility of alternative discussions in the judicial arena. Finally, this approach has a potential application in different regions and countries, as well as in different forensic problems, such as drug reports, homicide and other forensic investigations.

Table 8
Regression Vector: coefficients for each variable to compose RR-vector.

Variable	Coefficient
V01	−0.046
V02	0.051
V03	−0.050
V04	0.018
V05	0.073
V06	**0.144**
V07	0.051
V08	0.056
V09	0.040
V10	−0.027
V11	0.031
V12	0.055
V13	**0.198**
V14	0.090
V15	0.049
V16	0.077
V17	0.083
V18	0.069
V19	0.072

Bold values indicate the most important variables to describe RR.

Ethical approval
None.

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Conflict of interest
None declared.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.jflm.2014.06.004.

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